Spatialities of Missing Females and Daughter Disliking Societies

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I. Introduction

The prevalence of the missing girl child remains a significant aspect of Indian demographics. Literature highlights the pervasiveness of this issue with no indication of improvement. Historically, the phenomenon of Missing Females – elimination of girl child in reaction to perceived loss of status/pride/honour – has been primarily concentrated in the northern and northwestern regions of the country (Miller, 1981; Sopher, 1980; Agnihotri, 2000, 2003), later extended across various regions of the country (Agnihotri, 2000; Siddhanta et al., 2014, 2017), particularly following the route of economic prosperity (Agnihotri, 2000; Siddhanta et al., 2003). Spatial theories have been proposed to explain this pattern as a form of cultural diffusion, illustrating the processes through which new ideas and technologies propagate within a society (Nandy, 2008).

To begin with we ask the question that whether this social menace - Missing Females as phenomenon is spreading like a disease and thereby has become a feature of the human geography, i.e., is there an aspect of diffusion? If yes, then where and how much is the extent of its spread? To answer such questions, we argue that measuring spatial dependence or spatial autocorrelation and subsequent mapping of child sex ratios should be the relevant tools. Here, the diffusion is one that of a bad practice that also requires social sanction. And as these processes are spatial, we expect high spatial dependency in statistics such as female to male ratio among child population (0-6 years). But with technological development, the notion of sanction has narrowed in its essence as now the sanction is not required from the society, but from the family thereby providing sanitization to this criminal activity of female feticide.

The advent of sex-selective technologies, including ultrasound and amniocentesis, has dramatically altered the landscape of sex ratio imbalances. George (2006) notes that advancements in non-invasive prenatal testing - allowing determination of the sex of fetus as early as six weeks into pregnancy when combined with market-driven promotion of sex selection and libertarian ideologies advocating for unrestricted personal choice, has significantly eroded ethical boundaries and the practices have reached genocidal levels. Studies by Arnold et al. (2002) and Jha et al. (2006) provide estimates of the widespread use of these technologies for sex selection – Arnold et. al. (2002) notes that in the late 1990s more than 100,000 sex-selective abortions of female fetuses were being performed annually in India, while Jha et al. (2006) estimates that in past 2 decades (till 2006) abortion of some 10 million female fetuses have taken place. Kulkarni (2012) has calculated that around 400,000 sex-selective abortions are performed each year. More recently, Kulkarni's UNFPA Report (2020) confirms that the situation has remained unchanged. The diffusion of these technologies has been aided by weak regulatory frameworks and the commercialization of healthcare services in India. The spatial distribution of sex ratios reveals significant regional disparities. Agnihotri (2000), Guilmoto (2008), Siddhanta (2009) demonstrate that certain regions, particularly in North-West India, serve as "epicentres" of sex discrimination. These areas are characterized by high levels of masculinity in child sex ratios and are often associated with economic prosperity. This spatial dimension of sex ratio research underscores the importance of considering regional and contextual factors in understanding the dynamics of gender discrimination (Siddhanta, 2009).

These phenomena though rely on diffusion of technology and its subsequent adoption for malpractice, but can even locate itself into a new epicentre wherever necessary arrangements can be made possible depending on convenience. Relevant mapping of decadal child sex ratios using off the shelf techniques should be able to illustrate the same across time and space. However, what is important is to understand the forces that are responsible provisioning for the required sanction for indulging in these criminal activities resulting in a diseased environment for the democracy. Using multi-level (district and region) level analysis of administrative data – decadal census of 2001 and 2011, we demonstrate that the two primary force advocating legitimacy of this dire state is the lust for status – the *prosperity effect* and daughter dislike. Further, we find that both effects are confounded within the human geography indicating that their combined effect is manifesting a neo-culture of high-tech sexism[1] providing a persist-

1 A term coined by Sen (2001) referring to natality inequality wherein modern technologies are used to determine the sex of the unborn fetus and subsequent sex-selective abortion in order to eliminate the unwanted daughter.

ent spatial character that renders moral corruption making our social fabric dissoluble. The rest of the paper is divided in four sections. In section II, we measure the spatial dependence of masculinity of child demography demonstrating that this menace is spreading across regions as a social disease; in section III, we analyse the administrative data using spatial error model; section IV is construction of contour maps and section V is conclusion.

II. Missing Females: A Social Disease

If the Missing Females phenomenon is indeed a social menace, it should spread like a disease. Consequently, its measurement across any administrative unit must exhibit spatial dependence. Spatial dependence, or spatial autocorrelation, quantifies the extent to which the occurrence of an event in one area influences or makes more probable the occurrence of a similar event in neighbouring areas. This measurement serves two primary purposes: firstly, to gauge the strength of spatial autocorrelation, and secondly, to test the assumption of independence (randomness) of observations. A violation of the latter assumption can be interpreted through Tobler's first law of geography: *"Everything is related to everything else, but near things are more related than distant things"* (Tobler, 1970).

This spatial statistic heavily depends on the definition of neighbouring observations which is technically known as 'spatial weight matrix'. There is a gamut of techniques available to obtain this spatial weight matrix. The most primitive and easiest of them all are advanced by Moran (1948) and Geary (1954) which uses a binary notion of contiguity between various spatial units. Most frequently, these are rook contiguity or queen contiguity based on their movements in the game of chess. However, a chess board has a systematic grid, but the human geography we are working on is often arranged irregularly. For such situations, computing contiguity-based weight matrix would be faulty (Anselin, 1988). Moreover, such a contiguity only allows limited representations of spatial interactions which is inherently more complex. Anselin (1988) argued that such definition may not be sensitive '*... to a number of topological transformations in the sense that the same contiguity matrix can represent many different arrangements of the spatial units*'.

Cliff et al (1973, 1981) extended the idea of binary contiguity to a more general measure by incorporating distance. According to them, spatial weight matrix, $W_{ij} = \frac{p_{ij}^{\alpha}}{d_{ij}^{\beta}}$, where, d_{ij} is the distance between spatial unit i and j, p_{ij}^{α} is the proportion of the interior boundary of unit i, which is in contact with unit j, and α and β are the parameters.

However, such constructions are also not beyond criticism. They might not be appropriate whenever boundary of any area is not relevant to the statistic of interest (Anselin, 1988). Also, the construction of distance-based weight matrices is heavily affected by the topological quality of GIS data. For instance, inaccuracy in storing polygon/vertices may erroneously generate them as islands or other connection structures. Moreover, distance-based weight matrices often require a threshold distance value which is difficult to determine particularly when there is high spatial heterogeneity. Chi et al (2008) provides an extensive literature survey where they conclude that k-nearest neighbour structure is more appropriate for analysis based of administrative unit data at the lowest level. Though there is no agreement in the literature regarding the appropriate number of neighbours for constructing the most relevant weight matrix. However, Anselin (1988) argues that the choice of weight matrix should be based on spatial interaction theory. As the null hypothesis of spatial autocorrelation is spatial independence, the power of the test is be maximized by using a weight matrix associated with the relevant alternate hypothesis. Therefore, the optimum spatial weight matrix must follow a data driven approach, which is to select the matrix depending on the basis of highest spatial autocorrelation coefficient, as such an approach is embedded in the theory driven approach of test for spatial dependence. Using the weight matrix we then measure the spatial dependence using Moran's index also commonly known as Moran's I. Formally, $I = \frac{n\sum_i \sum_j W_{ij} Y_{ij}}{S_0 \sum_i Y_i^2}$, where, W_{ij} is the weight matrix, Y_{ij}, the measure of proximity in some other dimensions. Here, $Y_{ij} = (y_i - \overline{y})(y_j - \overline{y})$, $Y_i^2 = (y_i - \overline{y})^2$ and $S_0 = \sum_i \sum_j W_{ij}$. Under the null hypothesis of no spatial autocorrelation, I approaches to 0 for large n and under its alternative hypothesis, I approaches to (+1) or (-1), i.e. high positive and negative[2] autocorrelation respectively.

2 Negative spatial autocorrelation (known as spatial outlier) is a very rare phenomenon particularly in social science.

Note here that significant[3] spatial autocorrelation does not always imply spatial homogeneity. As Moran's I approaches 1, it indicates a tendency of clustering whereas -1 would indicate the tendencies of dispersion. Table 1 reports the Moran's I statistic of child sex ratio (0-6 years) for 1991, 2001, and 2011. Analysing the trend of spatial correlation over the decades indicates that from 1991 to 2001 clustering was increasing, which is represented in the table 1 by increase in Moran's index. However, in 2011 the value of the index decreases indicating that now there are new regions which are also becoming centres for masculine child sex ratios and should be a matter of concern as child sex ratios is related to violence and aggressive behaviour in the space. (Nayak, 2024). In order to dig deeper into this link of child sex ratios and violence, our first task would be to analyse the pattern of child sex ratios and for the same we argue that using mapping techniques will serve as a useful tool for such an analysis.

Table 1: Moran Index - FMR (0-6 years)

k-nearest neighbour	1991	2001	2011
2	0.803	0.865*	0.828*
3	0.805*	0.852	0.816
4	0.796	0.841	0.798
5	0.792	0.836	0.786

Data Source: Census of India tables 1991, 2001, 2011

III. Missing Females and the Daughter Disliking Society

In this section, we analyse the administrative data to uncover the determinants of missing females. Consider the following equation

$$\text{FMR}(0-6)2011_d = \alpha_0 + \alpha_1 FertilityDecline_r + \alpha_2 CWR(2001)_r + \alpha_3 Prosperity_d + controls + error$$

where $\text{FMR}(0-6)\,2011_d$ is the females per thousand males between 0-6 years of age in district d, $CWR(2001)_r$ is the child women ratio of region r in 2001, $FertilityDecline_r$ is the decadal change in child women ratio

3 The statistical significance of Moran's I can be judged on the basis of Normal distribution with, $Z = \frac{I - E(I)}{S_{Error}}$ where I is the Moran's index, $E(I)$ is the expected value of I and S_{Error} is the standard error.

$[CWR(2001)_r - CWR(2011)_r]$ and $Prosperity_d$ is the first component of the PCA score for assets which is further standardized for zero mean and unit standard deviation.

Column (1) and (2) of Table 2 reports the OLS estimate of the coefficients of the above equation. In the first column we omit the controls. The results of these baseline models suggest that regions characterized by relatively high prosperity and higher fertility rates, as well as areas experiencing further decline in fertility, are significantly associated with a more masculine child demography. This analysis suggests that regions experiencing fertility decline in later stages are not necessarily undergoing social progress. Rather, this decline is driven by societal pressure to adhere to norms that favour smaller family sizes achieved by ensuring the birth of male children. The advancement of medical technology has made it easier to determine the sex of the fetus, and, coupled with widespread aversion to daughters, this information has facilitated sex-selective practices. Further analysis confirms the emergence of daughter aversion as a cultural force.

Table 2: Determinants of Missing Females

	(1)	(2)	(3)	(4)
	FMR(0-6) 2011	FMR(0-6) 2011	FMR(0-6) 2011	FMR(0-6) 2011
	OLS	OLS	SEM-GMM	SEM-GMM
Fertility Decline	-30.62***	-25.73**	3.001	16.344
	(11.59)	(10.97)	(14.264)	(13.077)
CWR 2001	-33.31***	-30.31***	-13.791***	-23.618***
	(3.724)	(3.652)	(5.127)	(4.161)
Prosperity	-20.39***	-26.37***	-2.677	0.435
	(1.708)	(2.423)	(2.530)	(2.485)
Missing Girl Child (2001)†				-0.616*** (0.058)
lambda			0.868***	0.731***
			(0.025)	(0.042)
controls		✓	✓	✓
_cons	1050.8***	1107.8***	1035.88***	1091.62***
	(12.05)	(20.34)	(24.803)	(19.897)
N	636	636	636	636
adj. R^2	0.235	0.375		
pseudo R^2			0.253	0.664

† Quantifies missing girl child in region r for every thousand boys (0-6 years) from 2001.

Standard errors in parentheses. Control variables include female and male literacy, urbanization, proportion of non-scheduled caste and non-scheduled tribe population. Column 4-5 reports a heteroskedasticity and spatial autocorrelation robust errors (KP-HET) following Kelejian et. al. (2010). Weight matrix is created using queen contiguity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the next two columns, we present the results from a spatial error model. The spatial component (lambda) of the model is significant, and its inclusion further confounds the effect of fertility decline as well as *prosperity effect*. This indicates that sex-selective behaviour, influenced by the *prosperity effect* and fertility decline, is motivated by a collective notion of daughter aversion prevalent within regional communities. Alongside the desire for elevated social status (*prosperity effect*), daughter aversion emerges as a significant demographic force that legitimizes sex selection practices. In the subsequent column, we introduce the variable *Missing Girl Child* $(2001)_r$ revealing an increased masculinization of child demographics in already affected regions. We note further confounding of *prosperity effect* and the effect of fertility decline on gender inequality suggesting that these processes are path dependent and that these driving forces are emerging as a cultural phenomenon casting a long shadow on the society. Also, here fertility decline is caused by the ability to select a male child through technology. Moreover, in a society where fertility decline is through stigma and not social change masculinity in child demography further exaggerates. For robustness we repeat the same analysis at a broader unit, i.e. regional level and even restricted for urban samples and find that the results are consistent.

IV. Construction of Contour Maps

Now that we have established that there are definite spatial forces resulting in spreading of this social disease – the phenomenon of Missing Females, our next step would be mapping analysis, and for the same we develop contour maps of decadal female to male (0-6 years) ratio.

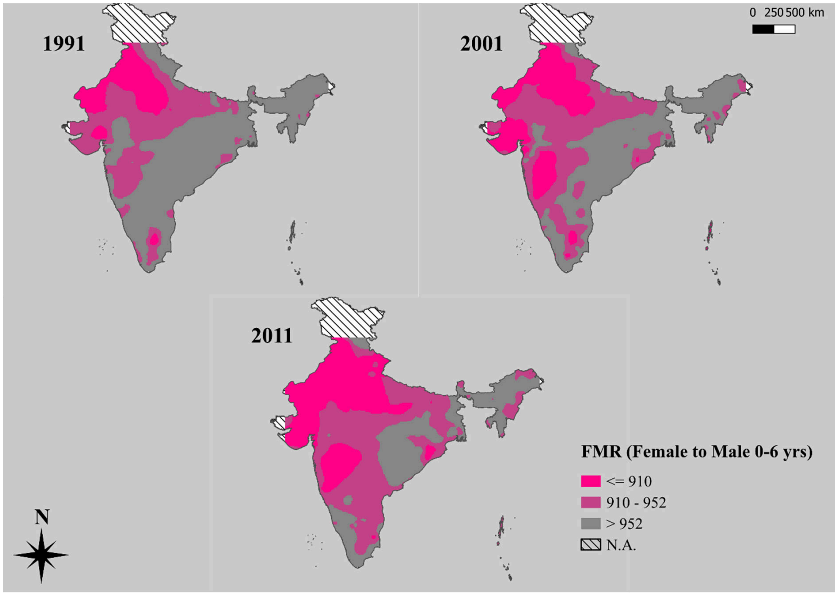
In this section we provide details regarding construction of contour maps. The spatial dimension of any attribute can be represented through a thematic map, of which the most commonly used is the Choropleth. The Choropleth shades or patterns the geographic area depending on the value of any variable. These geographic areas can be administrative units defined by their administrative boundary, and thereby are useful for analysis of those variables which are specific to administrative units such as election maps etc. However, for studies in demography, economics, gender, sociology, these maps may not be most appropriate since the focus is not on administrative units, rather boundaries can be traced according to the data pattern. And in such analysis isarithmic maps are more informative and appropriate (Siddhanta, 2009).

In order to create a contour map, we need to first specify the geographic coordinates from the digitized polygon maps based on the position of the centroid of each polygon and convert it to a point vector. We then employ a spatial interpolation technique for estimating unknown attribute values through contours using the known attribute values. Most broadly, there are two ways to operationalize the spatial interpolation – deterministic and geo-statistic (stochastic). Also, interpolation could be global as well as local. However, caution must be taken as deterministic local polynomial interpolation is sensitive to neighbourhood distance and small searching neighbourhood can also create empty areas in the prediction surface. Moreover, these deterministic local polynomial interpolation techniques can achieve desired accuracy only when the data is taken from a grid, i.e. they are equally spaced and the data values within the searching neighbourhoods are also normally distributed.

Another very useful local interpolation technique to predict the surface is to use stochastic or geo-spatial methods which employ statistical methods such as spatial autocorrelation and therefore is capable of producing predicted surface along with measures of certainty or accuracy of their predictions. The most common technique under this umbrella of geo-spatial interpolation technique is kriging. The assumption here is that the distance or direction between the data points is also based on the spatial correlation among them and this is then used to explain variation of the required variable say masculine child sex ratios over the surface.

Moreover, there are two types of kriging methods, ordinary and universal. The ordinary kriging the most widely used method assumes a constant unknown mean. Universal kriging on the other hand assumes that there is an over riding trend in the data which can be modelled by a deterministic function - a polynomial. Once specified, the polynomial is subtracted from the given value at the points and the subsequent autocorrelations is then modelled using the random errors. After fitting the model to random errors and before making the predictions, the polynomial is added back in order to produce a meaningful map surface. Predictions typically use weighted least square techniques. However, universal kriging should only be used when we are sure that there is an over-riding trend in the data and there is some scientific justification for the same. Therefore, we will consider it for mapping purpose only if it provides a better fit, i.e. when it is more optimal as well as valid compared to its ordinary counterpart.

Figure 1: Female to Male ratio (0-6 years) - 1991, 2001, 2011



Note: FMR refers to Female to Male ratio – female per 1000 male (0-6 years). Source : Census of India tables.

Another important point about kriging is that it is based on regionalized variable theory, that assumes that the spatial variation is statistically homogeneous throughout the surface. This notion of spatial homogeneity is central to regionalized variable theory and requires a second order stationarity. There are two types of stationarity - the first one is the mean stationarity where it is assumed that the mean is constant between samples and is independent of location. The second type of stationarity or the second order stationarity is also known as the intrinsic stationarity for semivariograms (that represents the autocorrelation function). It is the assumption that covariance is same between any two points that are at same distance and direction. This is very important for estimating the dependence rule and therefore, which would further allow us to make predictions. One shortcoming of ordinary as well as universal kriging is when the data is non-stationary, i.e. these methods cannot account for the error incorporated while estimating the under lying dependence structure or semivariogram.

As India is also a collection of heterogenous sub-spaces, it would be wrong to assume homogeneity in the process of diffusion across the subcontinent without testing it. One way to test the same would be to use an interpolator designed for non-stationary data and then compare the fit of such a model with local polynomial interpolation, and ordinary or universal kriging predictions. One such interpolation technique is Empirical Bayesian Kriging which can handle atleast a moderately non-stationary data by accounting for the error in estimating the under lying semivariogram. Empirically Bayesian Kriging uses subsetting and simulations for calculating the semivariogram parameters. These parameters are estimated using restricted maximum likelihood. The data is first divided into overlapping subsets of some specified size. In each subset, semivariograms are estimated using the following methodology.

- Step 1 - Semivariogram is estimated from the data of the subset.
- Step 2 - This semivariogram is used to simulate new data at each point or location in the subset.
- Step 3 - Another semivariogram is estimated from the stimulated data.
- Step 4 - Step 2 and Step 3 are repeated for some specified number of times and in each repetition the semivariogram estimated in Step 1 is used to simulate the new dataset at the locations.

Running this process for several times creates a large number of semivarioigram for each subset and together they form an empirical distribution of semivariograms. For each prediction location, the prediction is calculated using a new empirical semivariogram distribution which is generated by combining the individual semivariograms from the semivariougram distributions in the locations neighbourhood. The semivariogram from each subset are weighted by the number of neighbours they contribute to the prediction, thereby formulating into an intrinsic random function that serves as the kriging model. Table A1 reports various statistics to identify the best and most appropriate mathematical function of the empirical bayseian kriging. After identifying we use the same to generate the respective maps (figure 1). The map highlights the spread of missing females phenomenon across the geography engulfing newer areas.

V. Conclusion

The phenomenon of Missing Females in India, especially among the child population, exhibits a significant spatial autocorrelation, affirming its nature as a social menace spreading akin to a disease across different regions. This study employs spatial dependence metrics and mapping techniques to unravel the diffusion patterns of this demographic issue, suggesting that it not only persists but also proliferates in newer areas. The results from the Moran's I statistic underscore a concerning trend of clustering, indicating an expansion of regions with skewed child sex ratios, which now serve as new epicentres of this demographic imbalance.

Through a multi-level analysis of administrative data from the decadal census of 2001 and 2011, our findings elucidate two primary forces propelling the legitimacy of this dire state: the lust for status (*prosperity effect*) and the pervasive cultural aversion towards daughters. The accessibility and misuse of medical technologies for sex-selective practices have sanitized the crime thereby facilitating this phenomenon further.

The spatial error model further substantiates the interplay of these forces revealing a complex neo-culture of high-tech sexism. This culture not only perpetuates but also normalizes gender-biased sex selection, fostering a persistent spatial character of moral corruption within Indian society. The significant spatial component in our model emphasizes the regional diffusion of sex-selective behaviour, driven by collective regional and communal ideologies.

In summary, the entrenched daughter aversion and *prosperity effect* within India's spatial dynamics reveal a profound demographic and moral crisis. This study underscores the urgent need for targeted policies to curb technological misuse and challenge deep-seated cultural norms. Disrupting the spatial diffusion of gender bias (restrictive policies), fostering gender equality, and reshaping societal values towards daughters are imperative. These findings contribute significantly to the discourse on gender demographics and provide a robust foundation for future efforts to combat this pervasive social menace.

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Appendix

Table A1: Prediction Errors for various Contouring Techniques

1991	Epanechnikov	Pentaspherical	Rational Quadratic	J-Bessel	Pentaspherical	Exponential Detrended
RMS	16.632	14.999	14.885	15.338	15.212	14.382*
RMSS	0.989	1.02	912.115	1.012	1.018	0.995*
ASE	16.993	15.166	0.017	15.5*	15.395	14.134
MSE	0.059	0.004	1.099	0.0033	0.001*	-0.005
2001	Gaussian	J-Bessel	K-Bessel	J-Bessel	J-Bessel	K-Bessel
RMS	19.099	18.319	17.619	18.364	18.817	17.321*
RMSS	0.049	0.90	746.949	0.918	0.911	1.012*
ASE	19.175	20.851	0.024	20.649	20.874	17.391*
MSE	0.0488	-0.004	-2.387	-0.008	0.011	-0.001*
2011	Quartic	J-Bessel	Circular	J-Bessel	J-Bessel	K-Bessel
RMS	18.627	18.008	17.868	17.998	17.829	16.59*
RMSS	0.996*	0.928	812.417	0.928	0.894	0.98
ASE	18.634*	19.697	0.022	19.672	20.224	17.168
MSE	0.032	-0.003*	0.069	-0.005	0.003	-0.004

Note- Anisotropic, Optimised. RMS - Root Mean Square Error, RMSS – Root Mean Square Error Standardised, ASE - Average Standard Error, MSE – Mean Square Error.
Data Source: Census of India tables 1991, 2001, 2011